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Capabilities, diversification & economic dynamics in European Regions

Jan Fagerberg[1] · **Martin Srholec**[2]

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Abstract
What determines the differences in economic performance across European regions? In addressing this question, this paper takes inspiration from two different approaches. One approach highlights the role of capability-building, of a technological or social nature, while another perspective emphasizes the potential advantages of proximity and, hence, a relatively diversified economic structure, for regional economic performance. The paper argues that the impacts of capability-building and diversification on regional economic development need to be assessed jointly. Using information for 261 regions at NUTS2 level in 27 European countries in the 2000s, novel data sources are exploited to construct measures of technological and social capabilities, which are combined with indicators of related and unrelated variety in the analysis of regional economic dynamics. The results suggest that capability-building play a key role in regional economic development while the results for diversification are more mixed.

Keywords Technological capability · Social capability · Related variety · Unrelated variety · Regional economic development · Europe

1 Introduction

What determines the differences in economic dynamics across European regions? In addressing this question, this paper takes inspiration from two different approaches on this

✉ Martin Srholec
martin.srholec@cerge-ei.cz

Jan Fagerberg
j.e.fagerberg@tik.uio.no

[1] Center for Technology, Innovation and Culture (TIK), University of Oslo, Sognsveien 77, 0855 Oslo, Norway

[2] CERGE-EI, a joint workplace of Charles University, Economics Institute of the Czech Academy of Sciences, Politickych veznu 7, 111 21 Prague 1, Czech Republic

issue, both of which focus on the role of innovation and diffusion of technology and the conditions for getting the most out of that. One approach, originally based on studies of how poorer countries may catch up economically (or fail to do so), but subsequently applied to regions as well (Crescenzi et al., 2007; Fagerberg et al., 2014; Fagerberg & Srholec, 2017), particularly highlights the role of capability-building, of a technological or social nature, for regional economic development. Another perspective, drawing on economic geography and evolutionary thinking, emphasizes the potential advantages of proximity (of knowledge holders etc., see Boschma, 2005) and, hence, a relatively diversified economic structure (Frenken et al., 2007), for innovation, learning and economic performance at the regional level (see Whittle & Kogler, 2020 for an overview).

Are these approaches alternative explanatory frameworks or do they complement each other? Recent research on regional diversification in Europe indicates that social and institutional factors, what we following Abramovitz (1994b) call social capabilities, do indeed influence diversification processes (Cortinovis et al., 2017). Moreover, the economic impact of diversification has been shown to be contingent of how technologically advanced regions are (Cortinovis & van Oort, 2015). This leads us to believe that capability-building and diversification both influence regional economic development, and that their impacts need to be assessed jointly, which is what this paper aims to do.

The structure of the paper is as follows. Section 2 surveys the literature on the roles of capability-building and diversification, respectively, in regional economic development. Based on the discussion Sect. 3 goes on to measure capabilities, of a technological and social nature, at the regional level in Europe, with the help of factor analysis on a broad set of relevant indicators. The analysis covers 261 regions at NUTS2 level in 27 Europeans countries in the first decades of the new millennium. The resulting measures, combined with information on diversification from other sources, are then used in a regression analysis on economic dynamics in the subsequent period, the findings of which are reported in Sect. 4. Section 5 considers the lessons from the analyses.

2 Roles of capabilities & diversification in regional economic development

This section discusses what can be learnt from the existing literature on the roles of capabilities and diversification in regional economic development. The focus on capabilities in long run economic development comes from scholars in economic history, business-studies and development research, while economic geographers with an evolutionary orientation have examined the role of diversification in these processes.

2.1 Capabilities

What it takes for less developed countries or regions to catch up economically has been a central research issue among economic historians and development scholars for at least half a century.

The economic historian Gerschenkron (1962) pointed out that although the existence of more advanced technology in use elsewhere (a so-called ‘technology gap’) represents ‘a great promise’ for backward regions, turning this promise into reality is far from easy, but on the contrary requires substantial efforts and institution-building. Abramovitz (1986), arguing along similar lines, used the term ‘social capabilities’ for the collective assets that a backward country or region need to take advantage of technology gaps. When defining it, he cast the net rather broadly, including aspects such as skills, infrastructure, the legal system, governance, and norms/culture, e.g., honesty and trust (Abramovitz, 1994a, 1994b). Thus, the concept social capability includes—but extends much beyond—what is commonly called “social capital”[1].

A related term, ‘technological capabilities’, i.e., the capabilities that firms in backward regions have to acquire in order to be competitive, was suggested by the Korean development scholar Kim (1980, 1997). Kim distinguished between three types of technological capability: production capabilities; investment capabilities and innovation capabilities. According to Kim production capabilities are required to produce goods that satisfy global standards, investment capabilities are necessary to move into new areas, while innovation capabilities are required for developing new products and services and compete head on with foreign firms at the frontier. Hence, following this view, for a firm, region or country to continuously improve its position (reduce the technology gap), continuous upgrading of technological capability will be necessary (Bell & Pavitt, 1993).

Although initially developed for analysis of firms, the technology capability concept has also been applied at more aggregate levels, e.g., “national technological capability” (Lall, 1992). Arguably, firms’ performances depend to a crucial extent on the characteristics of the environment in which they operate. For example, a firm’s technological capabilities do not only depend on its own activities but also the capabilities of its customers, suppliers and other firms and organizations with which the firm is in regular contact, that is, the broader (national or regional) innovation system in which it is embedded (Lundvall, 1992; Braczyk et al., 1998).

Defining and measuring capabilities at different levels of aggregation remain a challenge. Nevertheless, over the years the availability of data on many potentially relevant aspects has improved significantly, and several attempts have been made—particularly at the country level—to exploit this to measure capabilities, often by weighing together different (albeit related) information (Archibugi & Coco, 2005). Fagerberg and Srholec (2008) used factor analysis on various indicators on technological and social capabilities for 115 countries between 1992 and 2004 to arrive at a smaller number of variables, which they then used to explain economic growth. The research suggested that capability building has a powerful effect on economic performance, and these results were found to be robust to inclusion of a number of control variables reflecting differences in nature, history and culture. Although, the research reported above applies mostly to the national level, some studies have attempted to take into the account the role of technological and social factors at the regional level as well (Crescenzi et al., 2007; Fagerberg et al., 2014; Fagerberg & Srholec, 2017; Cortinovis et al., 2017). This paper extends these previous studies by among others (1) including a broader range of indicators for technological and social factors and (2) exploring the relationships between these factors and productivity growth.

Another strand of literature that also emphasizes the role of capabilities for economic development focuses on the interaction between capabilities and the structure of production and, particularly, trade (Hidalgo et al., 2007; Hidalgo & Hausmann, 2009). The more sophisticated the products are, the argument goes, the more advanced capabilities need to

[1] For an overview of the literature on social capital, see Portes 1998.

be. Hence, following this view, one can make inferences about the development a country's (or region's) capabilities from how sophisticated its trade structure is. Since—for many (developing) countries—trade data are widely available at a highly disaggregated level, while information on capabilities is scarcer, this may be a useful approach in some instances. However, in the case of European regions, production data are very aggregated and trade data virtually non-existent. Hence, for our purpose it is more fitting to measure capabilities directly through identifying relevant indicators.

In fact, in recent years, the quality and availability of regional data on different aspects of capabilities have improved significantly. For example, regional statistics on R&D activities, protection of intellectual property rights (IPRs), and university attainment have become readily available through statistical agencies, including Eurostat (2020). Moreover, new measures of the broader social fabric that condition advances in technology have been assembled for a large number of regions by researchers. For instance, Charron et al. (2015) provide survey data on governance at the regional level that includes information on the perceived extent of corruption, impartiality, and quality of public services. Another relevant source is the European Value Study (2008), from which can be derived unique insights on regional differences in values, attitudes and social activities of people. In this paper, we integrate this new evidence with the literature on capabilities to derive new insights on regional development.

2.2 Diversification

Diversification is the opposite of specialization. In economics increased specialization (and, hence, trade) is generally thought of as associated with higher prosperity, through improved resource allocation and/or exploitation of economies of scale (Corden, 1984; Dixit & Norman, 1980; Dowrick, 1997). This goes both for specialization across industries (so-called inter-industry specialization), often assumed to reflect differences in factor supply (that is, so-called comparative advantage), or specialization at a finer level within a specific industry (so-called intra-industry specialization), which may for example have to do with differences in knowledge, demand, tastes etc.

Nevertheless, to the extent that proximity is good for learning and innovation,[2] which are widely recognized as important growth drivers, increased specialization may arguably hamper productivity growth, because it reduces the opportunities for cross-fertilization of knowledge within regional boundaries.[3] How important is this in practice, and which effect prevails? Frenken et al. (2007), in an analysis on Dutch data from around the turn of the millennium, suggest that this can be tested with the help of an 'entropy measure' of diversification originally proposed by Jacquemin and Berry (1979). When applied to a region's production structure this measure splits the total variance in two parts, one associated with inter-industry specialization (which Frenken et al., (2007) term 'unrelated variety') and another, which is their main focus, reflecting the degree of specialization across more narrowly defined segments within industries (so-called 'related variety'). One of the hypoth-

[2] See Boschma (2005) for an overview and discussion of the role of proximity for innovation.

[3] However, as pointed out by one of the referees to this paper, according to the economist John Sutton's "bounds approach" to the study of technology and market structure (Sutton, 1998), low related variety may be expected to go together with high concentration in R&D-intensive industries, suggesting the possibility of high innovation and growth, i.e., counteracting the effect emphasized by Boschma (2005) and others.

eses entertained by Frenken et al. (2007), then, is that the less specialized (more diversified) a region is within industries (as reflected in 'related variety'), the better the opportunities for learning, innovation, and productivity growth should be. However, Frenken et al. (2007) fail to confirm this suggestion, as the relationship with productivity growth turns out be the opposite of what was expected (and significantly so).[4] Boschma and Iammarino (2009), in an analysis based on Italian data, similarly fail to confirm the hypothesis in two of three reported specifications. Cortinovis and van Oort (2015), in an analysis of European regions, also provide little support for the hypothesis, except for a subset of low-tech regions. The results for so-called "unrelated variety" are similarly discomforting. Thus, despite claims to the contrary (see, for example, McCann & Ortega-Argiles, 2015), the jury seems still to be out with respect to the economic effects of diversification.

These somewhat disappointing results may of course have to do with limitations of data or methods. For example, while the theory is about proximity of knowledge holders, the statistics used are for production, trade etc., and it cannot be excluded that knowledge bases and product (or industrial) classes do not necessarily coincide. To throw more light on this issue several studies have chosen to base the analysis on patent statistics (see, e.g., Castaldi et al., 2015; Miguelez & Moreno, 2018). Patent statistics have several advantages, e.g., wide availability, and the possibility to use information in patent documents to explore relationships between different patents (e.g., impact). Nevertheless, patents refer to inventions, not innovations, and are used much more frequently in some settings than in others (Griliches, 1990; Cohen, 1995). In fact, the global novelty requirement associated with patents implies that minor innovations/adaptations, which arguably make up the bulk of innovative activity world-wide, will not be counted simply because they are not patentable. Thus, particularly for regions below the global technology frontier, of which there are many in Europe, most of their innovative activities—as well other efforts to upgrade their economies and boost productivity growth—would get unrecognized by basing the analysis solely on this data source. To illustrate the extent of the problem, nearly one third of the regions in the sample of Miguelez and Moreno (2018), mostly low-income regions from the southern and eastern parts of Europe, had fewer than 30 patents annually over the years 2004–2006[5], a very low number indeed. Only around one fifth of the regions in their sample had more than 300 patents per year during this period, somewhat closer, perhaps, to what may be needed for calculating meaningful diversification indices. In fact, related variety as calculated by Miguelez and Moreno turns out to be strongly correlated with the number of patents in the region, probably because in samples with few patents, the computed entropy measure is sensitive to the number of observations.[6] Moreover, although using the same formula, there is virtually no correlation between Miguelez and Moreno's measure of related variety based on patents and another estimate of the same variable by Cortinovis and van Oort (2015) based

[4] Another hypothesis suggested by Frenken et al. (2007), and which was supported by their data, was that "related variety" would be positively correlated with increases in employment.

[5] According to the number of patent applications to the European Patent Office (EPO) by priority year in Regional science and technology statistics from Eurostat (2020).

[6] Pearson's correlation coefficient between the measure of related variety as calculated by Miguelez and Moreno (2018) and (the log of) the number of patent application to EPO (Eurostat, 2020) is 0.92 over the period 2004–2006 (based on data for 240 regions).

on employment statistics.[7] The latter may have its own problems and pitfalls, of course, but it does at least not suffer from the same bias as the patent-based measure.[8]

3 Capability-building & diversification in European regions

The aim of this section is to develop synthetic measures of technological and social capability for European regions, explore the relationships with economic development, and compare this with available information on diversification. For this purpose, we first assembled a broad set of relevant indicators from various sources, i.e., Eurostat's Regional statistics by NUTS classification (Eurostat, 2020), the EU-sponsored Regional Competitiveness Index (Annoni & Kozovska, 2010), the European Quality of Government Index (Charron et al., 2015) and the European Values Study (2008). This resulted in a list of 15 relevant indicators at the NUTS2 regional level[9], ranging from R&D and IPRs via skills to governance and social capital (e.g. trust), from the mid or late 2000s depending on availability. Hence, the measures developed here improve on the existing literature by taking into account a broader

Table 1 Results of factor analysis on capabilities (factor loadings)

	Technological capability	Social capability
Scientific publications	0.83	−0.08
Patents	0.69	0.12
Trademarks	0.65	−0.01
R&D expenditures	0.88	−0.04
Tertiary education	0.64	0.04
Professionals and technicians	0.74	0.15
Households access to internet	0.21	0.75
Early school and job market leavers	0.03	−0.83
Corruption	−0.03	0.96
Quality of public services	−0.08	0.98
Impartiality of public services	−0.07	0.95
Equal right to a job for immigrants	0.29	0.48
Trusting other people	0.08	0.74
Membership in voluntary organizations	0.10	0.72
Civic action	0.24	0.61

Note: Number of observations is 261; two factors with eigenvalue < 1 were detected, which explain 65.9% of total variance; extraction method: principal component factors; rotation: oblimin oblique; for definition of the variables, data sources and years see Table A1 in the appendix

[7] Pearson's correlation coefficient between the indices of related variety as calculated by Miguelez and Moreno (2018) for the years 2004–2006 and by Cortinovis and van Oort (2015) for the year 2004 is −0.15 (based on data for 240 regions).

[8] That is, in Cortinovis and van Oort (2015)'s sample, there is a sufficient number of employees in most regions to compute reliable indices.

[9] If appropriate the indicators are adjusted by the size of the region (i.e. per capita or as % of GDP etc.).

range of aspects and by using new and more recent data sources.[10] For more information on definitions of variables, data sources, years and composition of the sample, see the appendix to this paper and Tables A1–A3 there.

The results of the factor analysis are reported in Table 1. As is evident from the factor loadings the 15 indicators divide neatly in two dimensions, which we associate with technological and social capability respectively, with very little overlap. The first factor correlates strongly with variables known to be of importance for the technological competitiveness of firms (Fagerberg & Srholec, 2020), such as scientific excellence, R&D, IPRs, and a highly skilled labour force. In contrast, the second factor reflects the characteristics of the broader socio-economic system that surrounds (and hence also influences) the activities of private firms, such as the quality of governance (corruption, quality, and impartibility of public services), infrastructure (internet), social inclusion (immigrants, young people), civic participation and the prevalence of trust.

Figures 1 and 2 plot the resulting measures for technological and social capability against GDP per capita. The markers indicate whether the regions are located in the North, South or East of Europe broadly defined (for definitions see Table A2 in the appendix). For both

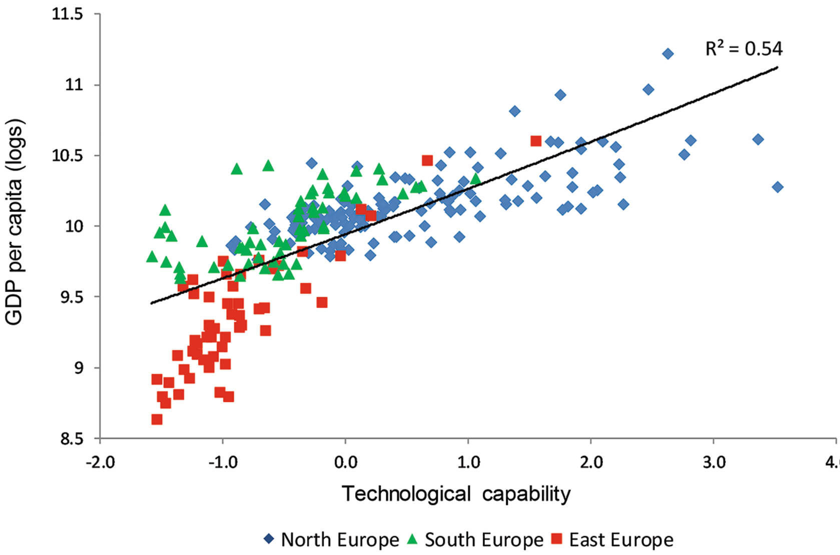

Fig. 1 GDP per capita and technological capability. (Note. GDP per capita is for the year 2005, technological capability is based on indicators from the nearest available year (see Table A1 in appendix for details))

[10] Note that, due to data availability, observations sometimes are from different years. For example, the European Value Study was carried out in different years in different countries. However, this problem should not be exaggerated. In fact, for the indicators associated with the technological capability measure, all observations are from a very narrow time span (the years 2004–2006). The same holds for the indicators associated with social capability (the years 2008–2010) with the exception of one single indicator (which is from the years 2004–2006). See Table A.1 in the appendix to this paper for more details.

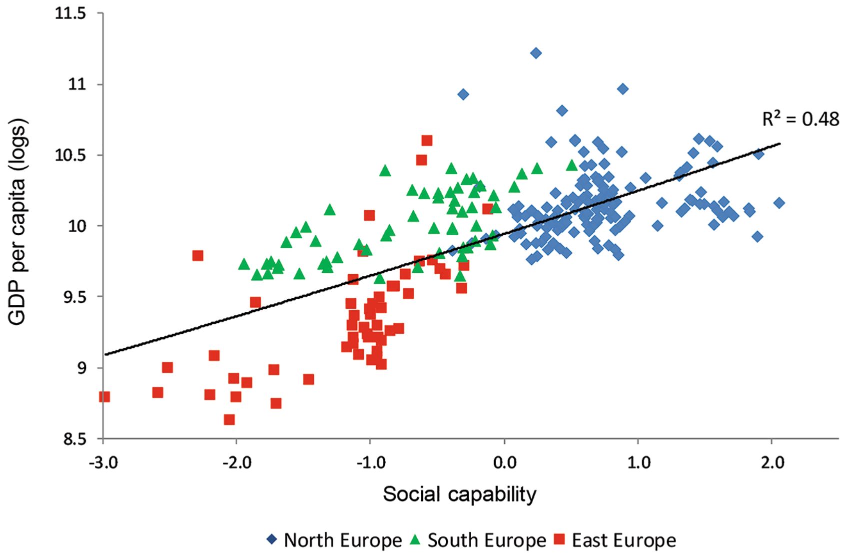

Fig. 2 GDP per capita and social capability. (Note. GDP per capita is for the year 2005, social capability is based on indicators from the nearest available year (see Table A1 in appendix for details))

indicators a strong, positive relationship with GDP per capita can be detected, confirming that capability-building and economic development do indeed go hand in hand.

Interestingly, the positive association with economic development does not hold to the same extent for diversification.[11] Figures 3 and 4 illustrate the relationships between measures of diversification (from Cortinovis and van Oort 2015) and GDP per capita. The relationships turn out to be quite weak in both cases. In fact, so-called related variety (within-industry diversification), is—if anything—(weakly) negatively correlated with GDP per capita, while the opposite appears to be the case for unrelated variety (diversification across industries).

The figures also indicate that there is a good deal of heterogeneity across parts of Europe in the relationships between GDP per capita and the capability and diversification measures taken into account here. In particular, East Europe stands out from the rest of Europe. We will return to the implications of this heterogeneity below.

4 Regression analysis

Having developed measures of technological and social capability for European regions, and explored how capabilities and diversification vary with economic development, this section delves deeper into the relationships between capabilities, diversification and economic dynamics at the regional level in Europe. With economic dynamics we mean phenomena such as innovation, structural change (towards, say, more knowledge-intensive, high-value added activities), and productivity growth. However, a search for relevant infor-

[11] See also the correlation table in appendix (Table A4).

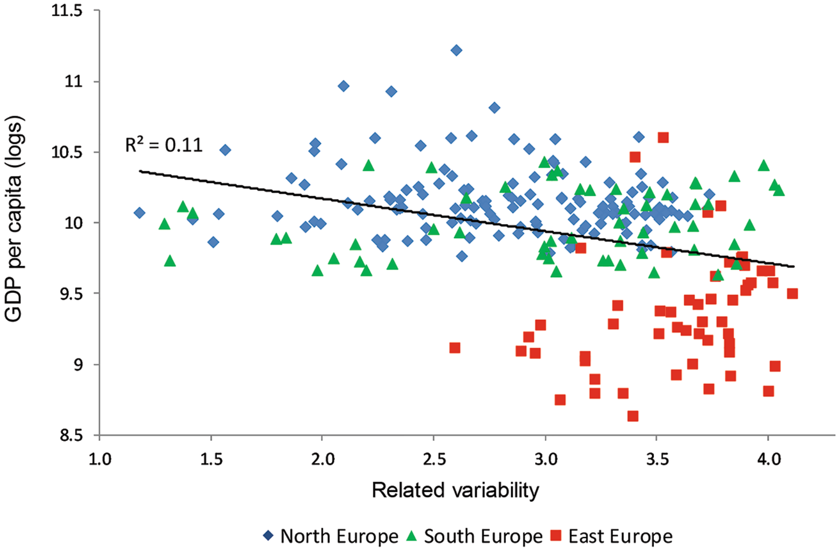

Fig. 3 GDP per capita and related variety. (Note. GDP per capita is for the year 2005, the diversification measures (from Cortinovis and van Oort 2015) are for the year 2004)

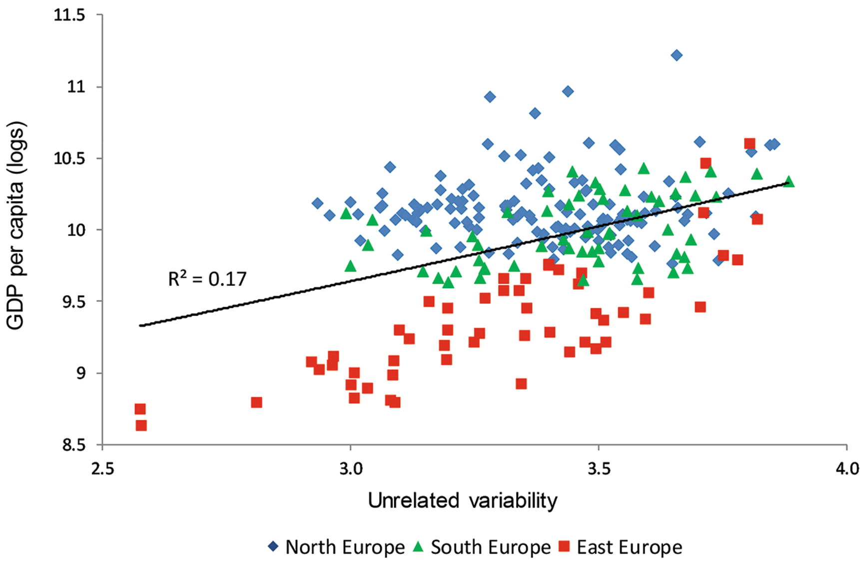

Fig. 4 GDP per capita (2005) and unrelated variety (2004). (Note. GDP per capita is for the year 2005, the diversification measures (from Cortinovis and van Oort, 2015) are for the year 2004)

mation revealed that there is not a wealth of indicators to choose from. For example, survey measures of innovation activity, i.e., the Community Innovation Survey (CIS), are difficult to compare across different waves of the survey (due to definitional changes) and countries/regions (due to the subjective nature of novelty adopted in the surveys).[12] Concerning the type of structural change considered here, regional industrial statistics are too aggregated to be of much value. Nevertheless, Eurostat (2020) has—based on employment statistics—constructed a measure of "knowledge-intensive sectors", covering activities with a high R&D content and/or skill structure, which may be included in the investigation. In contrast, data on productivity growth—or growth of GDP per capita—is widely available (European Commission, 2020), and will hence be an important variable in the analysis that follows.

When exploring the impact of capabilities and diversification on regional growth, we will apply a widely used methodology from the empirical growth literature, so-called Barro-regressions (Barro, 1991), which consist of regressing economic growth against initial GDP per capita and a number of other relevant factors. In this framework the initial GDP per capita variable measures the potential for catch-up (or convergence) [13], hence the estimated impact of this variable in the regression is expected to be negative (slowing down growth at the frontier and boosting growth among the laggards), while the other variables represent factors that are assumed to "condition" the ability to exploit the potential for growth entailed by the gap. As conditional factors we include the capability measures developed in this paper, the diversification indices from Cortinovis and van Oort (2015) and, finally, population density, a variable that is commonly used to account for agglomeration effects in analyses of regional growth.

Nevertheless, while there are good reasons to expect capabilities to influence economic dynamics, there may also—especially in the longer run—be a feedback the other way (from growth to capabilities). Furthermore, while we tried to find relevant indicators from the beginning of the period under analysis here, data availability led us in some cases to accept indicators from a later date (closer to the middle of our period). This holds in particular for indicators associated with the social dimension (social capability). Thus, although capabilities may be assumed to be relatively stable through time (change very slowly), some degree of interaction between economic dynamics (what we wish to explain) and capabilities (among the explanatory factors) cannot be excluded a priori, and it is important to keep this in mind in the discussion that follows.[14]

The results are reported in Tables 2 and 3, focusing on growth of GDP per capita and change in the share of knowledge intensive sectors, respectively. Three different tests are reported: (i) one with ordinary least squares (OLS); (ii) another using iteratively least squares which adjust for the impact of possible outliers based on the procedure suggested

[12] See Fagerberg et al. 2010 for a more detailed discussion. In addition, the regional CIS indicators are available at NUTS1 level only.

[13] As shown by Barro and Sala-i-Martin (2003, pp. 274–275), the inclusion of the GDP per capita variable may be consistent both with Solow's traditional neoclassical growth model (in which case the level of GDP per capita is assumed to reflect the capital intensity of the economy) and a Schumpeterian perspective (with a low GDP per capita indicating a high potential for diffusion).

[14] This is a well-known problem in the empirical literature on economic growth, see, e.g., the discussion in Durlauf et al. (2005). One remedy that is often recommended is the use of instrumental variables, i.e., exogenous variables that do not belong to the model but that are nevertheless correlated with the (endogenous) explanatory factors, provided that such instruments can be found. However, scarcity of data, and the fact we have already exhausted most relevant data sources in our search for indicators, prevent us from pursuing this line of analysis here.

Table 2 Regression results, GDP per capita growth

	(1)	(2)	(3)
Estimation method	Ordinary least squares (OLS)	Iteratively re-weighted least squares	OLS with standard errors clustered by countries excluding outliers
GDP per capita (logs)	-0.90^{***}	-0.91^{***}	-0.97^{***}
	(11.32)	(12.81)	(6.03)
Technological capability	0.42^{***}	0.38^{***}	0.47^{***}
	(6.06)	(6.17)	(5.95)
Social capability	0.18^{***}	0.29^{***}	0.31^{***}
	(2.81)	(5.21)	(2.81)
Related variety	0.35^{***}	0.35^{***}	0.40^{***}
	(7.54)	(8.44)	(5.91)
Unrelated variety	-0.12^{**}	-0.17^{***}	-0.17^{***}
	(2.49)	(3.89)	(3.31)
Population density (logs)	0.20^{***}	0.17^{***}	0.17^{**}
	(4.02)	(3.90)	(1.84)
F-test	54.84^{***}	68.94^{***}	19.99^{***}
R^2	0.58	0.45	0.65
Number of observations	249	249	229

Note: The dependent variable is GDP per capita growth over 2005–2017. The initial levels of the predictors are included. Beta values of the estimated coefficients reported. Absolute value of robust t-statistics in parentheses. *, **, *** denote significance at the 10, 5 and 1 per cent levels

Table 3 Regression results, change of knowledge-intensive sectors

	(1)	(2)	(3)
Estimation method	Ordinary least squares (OLS)	Iteratively re-weighted least squares	OLS with standard errors clustered by countries excluding outliers
Knowledge-intensive sectors	-0.16^{*}	-0.18^{**}	-0.20^{**}
	(1.69)	(2.10)	(2.70)
Technological capability	0.23^{**}	0.20^{**}	0.27^{***}
	(2.16)	(2.13)	(2.89)
Social capability	-0.21^{**}	-0.11	-0.15
	(2.54)	(1.51)	(1.36)
Related variety	0.28^{***}	0.24^{***}	0.30^{***}
	(3.90)	(3.73)	(3.30)
Unrelated variety	0.14^{**}	0.10	0.08
	(2.18)	(1.63)	(1.34)
Population density (logs)	0.17^{**}	0.09	0.11
	(2.35)	(1.36)	(1.34)
F-test	7.97^{***}	5.24^{***}	6.71^{***}
R^2	0.17	0.09	0.14
Number of observations	241	241	224

Note: The dependent variable is change of the share of knowledge-intensive sectors over 2008–2019. The initial levels of the predictors are included. Beta values of the estimated coefficients reported. Absolute value of robust t-statistics in parentheses. *, **, *** denote significance at the 10, 5 and 1 per cent levels by Li (1985); and, finally, (iii) OLS with standard errors clustered by countries and excluding outliers[15]. The latter method takes into account that regions are embedded in countries, with common institutions, governance, labour markets etc., which may influence regional performance in several ways. Beta coefficients are reported, which means that the variables are standardised to a common format, with a zero mean and a standard deviation of one.[16]

The results lend some support to both approaches, particularly capability-building. In fact, in the case with GDP per capita growth as dependent variable (Table 2), all variables in the test are significant at the 1 or 5% level, and correctly signed in all but one case, namely unrelated variety. Hence, while diversification within industries seems to be associated with higher growth, the opposite holds for diversification across industries. The latter is, as pointed out earlier (Sect. 2), consistent with what traditional economic theory would suggest (due to the assumed economic benefits from increased specialization). Table 3 reports the results of an attempt to explain the increase in the role of knowledge-intensive sectors in the economy, i.e., structural change towards more knowledge-intensive, high-value added activities. The tests, albeit predicting poorly, indicate that both technological capability and related variety play important roles in facilitating such changes.

The large majority of European regions have taken part in the process of European economic integration for many decades already, and many if not most benefits from this should be expected to be realized long ago. However, this does not extend to the former state-planned economies in Eastern Europe, dominated by the then Soviet Union, which joined the European Union (EU) from the mid-2000s onwards. It is possible that this enlargement of the EU gave a greater boost to productivity in the Eastern regions than elsewhere. Moreover, it cannot be excluded that various factors rooted in the past continued to influence the economic dynamics of Eastern European regions, and led their economies to behave differently from that of the more well-established parts of the EU. Some of the same considerations may perhaps apply to parts of Southern Europe (e.g., those governed by fascists regimes during large parts of the post-second world war period), although this may be considered less likely, as these countries have a much longer history of taking part in European economic integration.

To explore the possible influence of such contextual factors on GDP per capita growth, we include in Table 4 tests for differences in intercepts as well as slopes for the variables included in the model. Three different tests are reported. The first, which allows for different intercepts in the South, East and North of Europe, indicates that Eastern regions grew considerably faster from the mid-2000s onwards than regions in other parts of Europe, consistent with a positive "integration effect". Hence, joining the EU unleashed sources of growth that had not been allowed to flourish to the same extent under earlier arrangements. However, consistent with expectations, this pattern does not extend to regions in Southern Europe.

The next two regressions in Table 4 test for the possibility that not only intercepts but also slopes (i.e., the impact of the explanatory variables) may differ across parts of the continent. These regressions, and particularly the last one in which statistically insignificant

[15] Cook's distance with the conventional cut-off point at 4 / number of observations was used to exclude the outliers.

[16] Hence, the estimated coefficients refer to the impact of changing an independent variable by one standard deviation.

Table 4 Testing for differences between geographical areas, GDP per capita growth, OLS with standard errors clustered by countries excluding outliers

	(1)	(2)	(3)
GDP per capita (logs)	−0.56***	−0.31	−0.32**
	(4.06)	(1.17)	(2.09)
Technological capability	0.37***	0.27**	0.31***
	(4.04)	(2.22)	(2.94)
Social capability	0.34***	0.26**	0.36***
	(3.19)	(2.25)	(4.08)
Related variety	0.30***	0.31***	0.33***
	(4.33)	(4.73)	(5.01)
Unrelated variety	−0.16***	−0.18***	−0.13**
	(3.26)	(3.54)	(2.57)
Population density (logs)	0.09	0.05	.
	(1.09)	(0.50)	
East Europe	1.27***	1.57***	1.69***
	(3.03)	(3.09)	(6.44)
South Europe	−0.05	−0.12	.
	(0.15)	(0.36)	
East Europe x GDP per capita (logs)	.	−0.41	−0.53*
		(0.84)	(1.96)
East Europe x Technological capability	.	0.51	0.53*
		(1.47)	(2.04)
East Europe x Social capability	.	−0.07	.
		(0.22)	
East Europe x Related variety	.	−0.41**	−0.41**
		(2.31)	(2.28)
East Europe x Unrelated variety	.	−0.02	.
		(0.06)	
East Europe x Population density (logs)	.	0.00	.
		(0.00)	
South Europe x GDP per capita (logs)	.	−0.10	.
		(0.34)	
South Europe x Technological capability	.	−0.20	.
		(0.72)	
South Europe x Social capability	.	0.27	.
		(1.30)	
South Europe x Related variety	.	−0.03	.
		(0.24)	
South Europe x Unrelated variety	.	0.22**	.
		(2.17)	
South Europe x Population density (logs)	.	0.02	.
		(0.19)	
Constant	−0.22	−0.22	−0.30**
	(1.14)	(0.90)	(2.23)
F-test	17.35***	.	98.15***
R^2	0.75	0.78	0.77
Number of observations	229	229	229

Note: The dependent variable is GDP per capita growth over 2005–2017. The initial levels of the predictors are included. Beta values of the main estimated coefficients reported. Absolute value of robust t-statistics in parentheses. *, **, *** denote significance at the 10, 5 and 1 per cent levels variables are dropped (using a backward search)[17], indicate that differences in dynamics (if any) are concentrated in East Europe (see Table 4, last column). The most notable difference, significant at the % level, concerns the role of so-called related variety, which does not seem to be very consequential in East Europe.[18] Technological capability and the potential for diffusion (as measured by initial GDP per capita), on the other hand, play an even more important role in the East than in the rest of Europe (however, these difference are only significant at the 10% level).

From the mid-2000s onwards, the gap in income and productivity between the Eastern regions and the more developed regions in the North of Europe was gradually reduced, caused by 1,6% faster growth of GDP per capita per year in the East than in the North. This catch-up was, according to the estimates (based on regression 3 in Table 4), fueled by a combination of the possibility to benefit from more advanced technologies available elsewhere and the context-specific “integration effect “discussed above. However, according to the estimates, this catch-up would have been twice as fast had it not been for the very low levels of technological and social capabilities in East Europe. Hence, on the assumption that the “integration effect” will fade over time, which seems likely, East European regions will have to upgrade their technological and social capabilities in order to continue to catch up.

5 Concluding remarks

What are the implications of this study for our understanding of regional dynamics and, hence, the options policy makers face?

With respect to regional dynamics, two different approaches to the understanding of the phenomenon have been addressed, one stemming from economic history, development studies and innovation research, and another drawing on evolutionary perspectives on economic geography. The former approach led to a focus on capability-building, of a technological and social nature, while the latter similarly emphasized the beneficial nature of diversification, within or across industries, for successful regional economic development. Although earlier empirical research on these issues have mostly followed separate paths, and with variable results, this paper has argued that the two approaches should both be taken into account when investigating why regional dynamics differ.

Until recently, a complicating factor, particularly with respect to technological and social capabilities at the regional level, has been lack of relevant data for a sufficiently large group of regions. However, during recent years, the availability of relevant sources of information has improved a lot. Exploiting these opportunities, this paper has, with the help of factor analysis, developed new measures of technological and social capabilities of European regions, and combined these with indicators of economic diversification to explore the roles of both sets of factors in regional economic dynamics.

[17] A backward stepwise search for the best model specification was conducted using a criterion of 20% statistical significance level for exclusion and 10% statistical significance level for re-inclusion of a variable in the model.

[18] Note that the impact of related variety for Eastern European regions (regression 3 in Table 4) is the sum of the general effect (common to all regions), which is positive, and the specific effect for Eastern regions, which is negative. Hence, these two effects tend to cancel each other, since the absolute value of the estimate is about the same in the two cases, with the result that the total effect becomes negligible.

The results suggest that capability-building play a key role in regional economic development. Both technological and social capabilities are positively related to growth of GDP per capita, the relationships are strong, and robust to a whole battery of tests for other explanatory factors or possible biases. The results for diversification are more mixed. Diversification between industries (unrelated variety) appears, consistent with previous research on the matter, to be negatively associated with growth. Remembering that diversification is the opposite of specialization, this means that a more specialized economic structure is a positive factor for regional economic development, as received economic theory would indeed suggest. Nevertheless, diversification within industries—so-called related variety—is found to be positively associated with economic growth, consistent with what writers within the evolutionary economic geography strand have proposed but faced difficulties in demonstrating empirically.

However, the research presented here also shows that the positive relationship between diversification within industries and economic performance does not extend to all parts of the continent. In particular, it does not hold for the economically least developed regions, i.e., Eastern Europe. This finding clearly begs further questions about the generality as well as the policy implications of this relationship. A closer inspection of the results reveals that the regions that receive a strong, positive impetus to growth from so-called related variety are strongly concentrated in a limited number of areas, e.g., North Italy, South Germany and parts of the Iberian Peninsula.[19] Could it be that the virtuous dynamics associated with this type of industrial structure are the results of long, evolutionary processes in these regions that are not easily replicated elsewhere? Or that it is conditioned by various social, institutional and economic factors that may not exist—or work in the same way—in other contexts? It is beyond the scope of this paper to delve deeper into this issue, but these are important questions, that deserve further scrutiny in future research.

The key lesson for policy that comes out of this study is that capability-building, whether of a technological or social nature, is an essential ingredient in a successful regional economic strategy. This lesson holds for all regions in Europe, independent on development level, but may be of particular significance for the least developed ones, i.e., in East Europe, which—according to the results reached here—need to upgrade their capabilities if the process of catching-up with the richer regions in the rest of Europe is going to be sustained. Capabilities are important not only for innovation-based growth, but also for the capacity to absorb (and exploit) knowledge developed elsewhere, and the ability to engage in structural changes towards more promising (knowledge-intensive) activities. This may be even more critical in the years to come, during which the European economy is destined for a transition to an environmentally more sustainable state, which will require profound structural changes as well as opening up many new opportunities for regions in all parts of the continent.[20].

[19] The ten regions that according to the estimates (based on regression 3 in Table 4) receive the highest impetus to growth from related variety are Veneto, Lombardia and Emilia-Romagna in Northern Italy; Schwaben in Southern Germany; Cataluña, Comunidad Valenciana, Castilla-la Mancha and Aragón in Spain; and, finally, two Portuguese regions (Centro & Norte). Among the next ten, there are five more regions from Spain, two Southern German regions, and one Italian region, illustrating the strong geographical concentration of the phenomenon.

[20] See, e.g., https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en, accessed on 07/06/2021.

6 Appendix (data & sources)

Table A1 An overview of the variables

Definition	Unit	Source	Period	Estimated observations
GDP per capita Gross Domestic Product per head of population in Purchasing Power Standards (PPS).	PPS per capita	European Commission (2020)	2005 and 2017	0
Knowledge-intensive sectors Employment in high-technology manufacturing (21 and 26) and knowledge-intensive high-technology services (5 to 63 and 72); NACE, rev. 2 codes in brackets.	% of total employment	Eurostat (2020)	2008 and 2019	0
Scientific publications Counts of scientific publications indexed in Thomson Reuters Web of Science.	per million inhabitants	Annoni and Kozovska (2010)	2005–2006	0
Patents Patent applications to the European Patent Office (EPO) by priority year (as recorded in EPO Worldwide Statistical Patent Database "PATSTAT").	per million inhabitants	Eurostat (2020)	2004–2006	0
Trademarks European Union trade mark (EUTM) applications (based on data from the European Union Intellectual Property Office (EUIPO).	per million inhabitants	Eurostat (2020)	2004–2006	0
R&D expenditures Intramural expenditure on research and experimental development (R&D).	% of GDP	Eurostat (2020)	2004–2006	11
Tertiary education Individuals who have successfully completed education at the third level study (ISCED-97 version levels 5a, 5b or 6)	% of active population	Eurostat (2020)	2004–2006	1
Professionals and technicians Individuals who are employed in an S&T occupation: professionals (ISCO-88 COM code 2) or technicians and associate professionals (ISCO-88 COME code 3).	% of active population	Eurostat (2020)	2004–2006	1
Households access to internet Households with access to the internet at home.	% of total households	Annoni and Kozovska (2010)	2009	7
Early school and job market leavers Young people neither in employment nor in education and training (NEET)	% of population aged 15 to 24 years	Eurostat (2020)	2004–2006	5
Corruption Perceived corruption of public education, perceived corruption of public health care system, perceived corruption of law enforcement, amount of perceived bribery by others, respondent's own experience with bribery in public sector.	Index	Charron, et al. (2015)	2010	0

Table A1 (continued)

Definition	Unit	Source	Period	Estimated observations
Quality of public services Quality of public education, quality of public health care system, quality of law enforcement, perceived fairness of elections, perceived fairness and ability to report political corruption of media.	Index	Charron, et al. (2015)	2010	0
Impartiality of public services Impartiality of public education, impartiality of public health care system, impartiality of law enforcement, impartiality of public education, impartiality of public health care system, impartiality of law enforcement	Index	Charron, et al. (2015)	2010	0
Equal right to a job for immigrants Response to the following statement: "When jobs are scarce, employers should give priority to [nation] people over immigrants." 1 (agree), 2 (neither), 3 (disagree).	Index	EVS (2016)	2008–2010	4
Trusting other people Agreement with the following statement: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" 1 (Most people can be trusted), 0 (Can' t be too careful).	Index	EVS (2016)	2008–2010	4
Membership in voluntary organizations Belonging to voluntary organisations or activities (15 categories ranging from social welfare for elderly, handicapped or deprived people, political parties or groups, professional associations, youth work, sport or recreation to peace movement, etc.)	% of population	EVS (2016)	2008–2010	4
Civic action Response to a question about signing a petition. 1 (would never do), 2 (might do), 3 (have done).	Index	EVS (2016)	2008–2010	4
Related variety Measure of entropy in the distribution of employment shares within 21 sections of the industrial classification NACE.	Index	Cortinovis and van Oort (2015)	2004	0
Unrelated variety Measure of entropy in the distribution of employment shares among 21 sections of the industrial classification NACE.	Index	Cortinovis and van Oort (2015)	2004	0
Population density Population on 1 January per total area.	population per km2	Eurostat (2020)	2004–2006	0

Table A2 List of countries and regions

Country	Geographical area	Number of NUTS2 regions	Nuts2 region codes
Austria	North	9	AT11, AT12, AT13, AT21, AT22, AT31, AT32, AT33, AT34
Belgium	North	11	BE10, BE21, BE22, BE23, BE24, BE25, BE31, BE32, BE33, BE34, BE35
Bulgaria	East	6	BG31, BG32, BG33, BG34, BG41, BG42
Cyprus	South	1	CY00
Czech Republic	East	8	CZ01, CZ02, CZ03, CZ04, CZ05, CZ06, CZ07, CZ08
Denmark	North	5	DK01, DK02, DK03, DK04, DK05
Estonia	East	1	EE00
Finland	North	4	FI18, FI19, FI1D, FI20
France	North	22	FR10, FR21, FR22, FR23, FR24, FR25, FR26, FR30, FR41, FR42, FR43, FR51, FR52, FR53, FR61, FR62, FR63, FR71, FR72, FR81, FR82, FR83
Germany	North	38	DE11, DE12, DE13, DE14, DE21, DE22, DE23, DE24, DE25, DE26, DE27, DE30, DE40, DE50, DE60, DE71, DE72, DE73, DE80, DE91, DE92, DE93, DE94, DEA1, DEA2, DEA3, DEA4, DEA5, DEB1, DEB2, DEB3, DEC0, DED2, DED4, DED5, DEE0, DEF0, DEG0
Greece	South	13	EL30, EL41, EL42, EL43, EL51, EL52, EL53, EL54, EL61, EL62, EL63, EL64, EL65
Hungary	East	7	HU10, HU21, HU22, HU23, HU31, HU32, HU33
Ireland	North	2	IE01, IE02
Italy	South	21	ITC1, ITC2, ITC3, ITC4, ITF1, ITF2, ITF3, ITF4, ITF5, ITF6, ITG1, ITG2, ITH1, ITH2, ITH3, ITH4, ITH5, ITI1, ITI2, ITI3, ITI4
Latvia	East	1	LV00
Lithuania	East	1	LT00
Luxembourg	North	1	LU00
Malta	South	1	MT00
Netherlands	North	12	NL11, NL12, NL13, NL21, NL22, NL23, NL31, NL32, NL33, NL34, NL41, NL42
Poland	East	16	PL11, PL12, PL21, PL22, PL31, PL32, PL33, PL34, PL41, PL42, PL43, PL51, PL52, PL61, PL62, PL63
Portugal	South	5	PT11, PT15, PT16, PT17, PT18
Romania	East	8	RO11, RO12, RO21, RO22, RO31, RO32, RO41, RO42
Slovakia	East	4	SK01, SK02, SK03, SK04
Slovenia	East	2	SI01, SI02
Spain	South	17	ES11, ES12, ES13, ES21, ES22, ES23, ES24, ES30, ES41, ES42, ES43, ES51, ES52, ES53, ES61, ES62, ES70
Sweden	North	8	SE11, SE12, SE21, SE22, SE23, SE31, SE32, SE33
United Kingdom	North	37	UKC1, UKC2, UKD1, UKD2, UKD3, UKD4, UKD5, UKE1, UKE2, UKE3, UKE4, UKF1, UKF2, UKF3, UKG1, UKG2, UKG3, UKH1, UKH2, UKH3, UKI1, UKI2, UKJ1, UKJ2, UKJ3, UKJ4, UKK1, UKK2, UKK3, UKK4, UKL1, UKL2, UKM2, UKM3, UKM5, UKM6, UKN0

Table A3 Summary statistics (before imputing missing data)

	Period	Mean	St. dev.	Min	Max	Number of obs.
GDP per capita (logs)	2005	10.0	0.43	8.6	11.0	257
GDP per capita (logs)	2017	10.2	0.36	9.1	11.5	257
Knowledge-intensive sectors	2008	3.4	1.8	0.5	10.2	252
Knowledge-intensive sectors	2019	3.7	1.9	0.5	11.9	248
Scientific articles	2005–06	925.4	835.8	0.7	4206.0	261
Patents	2004–06	102.7	126.4	0	739.0	261
Trademarks	2004–06	79.8	95.8	0	1026.5	261
R&D expenditures	2004–06	1.3	1.1	0.1	6.3	250
Tertiary education	2004–06	23.3	7.7	7.7	47.8	260
Professionals and technicians	2004–06	25.8	6.4	12.3	48.8	260
Households access to internet	2009	63.1	17.4	23.1	95.3	254
Early school and job market leavers	2004–06	11.5	4.8	3.8	31.1	261
Corruption	2010	0.1	1.0	−2.8	1.9	261
Quality of public services	2010	0.1	1.0	−3.3	1.8	261
Impartiality of public services	2010	0.1	1.0	−2.9	1.7	261
Equal right to a job for immigrants	2008–10	1.7	0.4	1.0	2.7	257
Trusting other people	2008–10	0.3	0.2	0	0.8	257
Membership in voluntary organizations	2008–10	0.4	0.2	0.0	1.0	257
Civic action	2008–10	2.2	0.4	1.2	2.9	257
Related variety	2004	3.0	0.6	1.2	4.1	253
Unrelated variety	2004	3.4	0.2	2.6	3.9	253
Population density (logs)	2004–06	5.0	1.1	1.1	9.1	261

Table A4 Correlation table of the explanatory variables

	GDP per capita, (logs)	Knowledge-intensive sectors	Technological capability	Social capability	Related variety	Unrelated variety	Population density (logs)
GDP per capita, (logs)	1.00						
Knowledge-intensive sectors	0.52	1.00					
Technological capability	0.75	0.71	1.00				
Social capability	0.69	0.34	0.63	1.00			
Related variety	−0.34	−0.21	−0.21	−0.34	1.00		
Unrelated variety	0.40	0.37	0.24	0.10	0.09	1.00	
Population density (logs)	0.44	0.53	0.48	0.20	−0.15	0.26	1.00

Note: The number of observations is 249, except for correlations involving the variable for knowledge intensive sectors, for which the number of observations drops to 241 due to missing data on the latter

An overview of definitions and sources of the data is given in Table A1. Sample size and composition and reference periods were determined by the availability of data. For the indicators of technological and social capabilities we searched for data from the middle of the 2000s. However, due to lack of availability, some of the indicators are from the end of the decade. This holds particularly for indicators associated with social capability. Although the selected indicators have broad coverage, in some cases there were missing values that had to be estimated using the impute procedure in Stata/MP 15.1 (see the Stata 15.1 Manual for details). We based the estimation on data for the other indicators of technological and social capabilities used to construct the capability measures. The number of observations estimated by the procedure is given in the last column of Table A1.

All regions of the 27 countries located in the mainland Europe are included in the analysis (only small overseas and/or dependent territories, including Guadeloupe, Martinique, Guyane, Réunion, Ceuta, Melilla, Acores and Madeira, have been excluded). The regions refer to the second level of the division of the Nomenclature of Territorial Units for Statistics (NUTS2). Due to data limitations a combination of NUTS1 and NUTS2 regions was used in some cases. For instance, EVS (2016) data is at NUTS1 level in large countries that are divided in many regions (i.e. Germany, France, Italy, Spain and the United Kingdom), because the number of respondents was too small to derive reliable indicators at more detailed disaggregation. Due to changes in the NUTS2 classification some regions had to be merged using population as weight in averaging of the indicators (Brandenburg—Nordost (DE41) and Brandenburg—Südwest (DE42) merged in Brandenburg (DE40); Helsinki-Uusimaa (FI1B) and Etelä-Suomi (FI1C) merged in Etelä-Suomi (FI18); Inner London—West (UKI3) and Inner London—East (UKI4) merged in Inner London (UKI1) etc.). The full list of regions included in the analysis is given in Table A2.

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